Energy Policy 119 (2018) 282–293

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Time to get ready: Conceptualizing the temporal and spatial dynamics of formative phases for energy technologies

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ARTICLE INFO

Keywords:
Energy technology
Innovation system
Formative phase
Space
Hazard model

ABSTRACT

Implementing the Paris agreement to prevent dangerous climate change requires energy system transformation and rapid diffusion of low-carbon innovations. In this paper we investigate both the temporal and spatial dynamics of formative phases by which energy technologies prepare for growth. Drawing on a review of diverse literatures, we offer a definition of the formative phase which clarifies its scope and duration, and identifies its main technological and economic determinants. We use parametric hazard models to assess the relative strengths of these determinants on formative phase durations for a sample of 15 energy technologies diffusing over time in their respective initial markets. We find that substitutability has stronger effects in accelerating the end of formative phases than installed capacity and prices. We extend our analysis using nonparametric models to analyze the spatial diffusion of formative phase durations from initial to follower markets. We find that formative phase durations are long outside initial markets as well, showing only signs of acceleration in latecomer regions. Our results imply risks for policies trying to accelerate the diffusion of large innovations without ready markets in both initial and follower markets.

1. Introduction

The historical diffusion of energy technologies shows long periods of emergence within changing energy systems (Fouquet, 2016; Grubler et al., 2016). Energy technologies often take several decades in the early phase of their life-cycle prior to mass commercialization (Fouquet, 2014; Smil, 2010, 2016). This period is also known as the formative phase which can be defined in the following terms: a period marked by high uncertainties (Van de Ven, 2017), during which the conditions (standardization, performance improvement, etc.) are created for a new technology to emerge and prepare for large-scale commercialization (Jacobsson and Lauber, 2006; Arthur, 2009; Bento and Wilson, 2016). This interactive process of testing and improvement, and aligning market and user needs, tends to occur in a small number of initial markets. At the end of the formative phase the technology becomes ready to leave the initial markets and diffuse out into new markets (Binz and Anadon, 2018; Binz et al., 2017; Grubler, 2012). Understanding both the temporal and spatial dynamics that shape the formative phase is important in the debate on how to accelerate energy innovation for climate change mitigation (Winskel and Radcliffe, 2014).

Different strands of the literature cover the dynamics and determinants of the formative phase. These include the identification of key changes in the type of innovation (e.g., product vs process) (Huenteler et al., 2016; Taylor and Taylor, 2012), the strategic management of new industries around innovations (e.g. changes in companies' demography) (Peltoniemi, 2011; Gustafsson et al., 2016), and the dynamics of emerging systems in socio-technical transitions (Bergek et al., 2015; Markard et al., 2012; Geels, 2005).

In terms of what determines the duration of formative phase, studies in management science emphasize the role of demand variables, such as heterogeneity in price sensitivity and adopters' risk avoidance (Golder and Tellis, 1997; Tellis et al., 2003, 2012; Peres et al., 2010). The diffusion of innovations literature shows that diffusion rates depend on the characteristics of both the technology and the adoption environment (Rogers, 2003). These factors include: relative advantage (Mansfield, 1968; Chandrasekaran et al., 2013); compatibility and complexity (Arthur, 2009); disruptiveness, inter-relatedness and infrastructural needs (Grubler et al., 1999); and market size (Wilson, 2012).

Technology growth out of the initial markets is typically investigated with the focus on the constraints to adoption like distance in

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https://doi.org/10.1016/j.enpol.2018.04.015
Received 1 December 2017; Received in revised form 20 March 2018; Accepted 8 April 2018
Available online 03 May 2018

economic geography (e.g. Comin et al., 2012; Griffith et al., 2013), or interactions with existing contextual structures in system theories (Bergek et al., 2015; Hansen and Coenen, 2015).

In this paper we pose the question: *What determines the duration of formative phases for energy innovations in different markets?* We are interested both in initial markets (also: core, lead, first mover, early adopter) where formative phases prepare technologies for mass commercialization, and in follower markets (also: periphery, lag, late adopter) where accelerated formative phases may benefit from diffusion and spillovers. To understand the temporal dynamics of energy innovation within initial markets (growth over time), we apply a hazard model to a time series dataset of 15 diverse energy technologies (including both new and old, energy supply and end-use). To understand the spatial dynamics of energy technology diffusion between markets (growth through space), we use Kaplan-Meier curves to compare the dynamics of formation in follower regions.

The paper is structured as follows. Section 2 reviews the relevant literature on formative phases to identify definitions, patterns and determinants. Section 3 explains the methodology including data sources, model and variables. Section 4 applies the concepts and methods presented in the previous sections to measure formative phase durations across regions and to estimate the effect of the determinants in accelerating formative periods. Section 5 concludes and derives policy implications.

2. The formative phase

2.1. Definition

The term formative phase appears in the technological innovation system literature to designate the early period of diffusion during which new technologies are first used, improved and prepared for commercialization: "the value of this very first phase" is "in the opportunities [given] for experimentation, learning and the formation of visions" (Jacobsson and Lauber, 2006: 271). A similar concept is'era of ferment' which is used in the industry life-cycle literature to designate the period of intense rivalry and competition among variations, initiated by a technological breakthrough and eventually leading to the selection of a single dominant design (Abernathy and Utterback, 1978; Anderson and Tushman, 1990; Murmann and Frenken, 2006). Other terms have been suggested in marketing studies such as the 'time to take off' (Golder and Tellis, 1997; Tellis et al., 2003; Tellis and Chandrasekaran, 2012), which designates the period from product introduction to "substantial" growth. A related concept is the 'incubation time' (Kohli et al., 1999) which includes product development as well. Other terms are used in the innovation literature to designate the first period of development and commercialization including: 'embryonic' (Taylor and Taylor, 2012), 'nascent and emerging' (Markard and Hekkert, 2013), 'nurturing' (Smith and Raven, 2012), and 'installation' (Perez, 2002). The content of all these definitions can change in terms of the scope of technological change and the types of activities included.

The *scope* of technological changes expected to occur during the formative phase vary across different streams of the literature. The industry life-cycle literature focuses on modifications to the technology, the nature of innovation, and industry structure (Peltoniemi, 2011; Gustafsson et al., 2016). A technological opportunity introducing a new product encourages the entry of a large number of firms that will improve the quality of production and reduce prices (e.g. Agarwal and Bayus, 2002). According to this perspective, the transition to technological maturity is typically characterized by a shift from product to process innovation as product variety decreases and eventually a design becomes dominant (Abernathy and Utterback, 1978; Klepper, 1997).

The technological innovation systems (TIS) perspective considers the coevolution of technologies and context (Bergek et al., 2015). Bergek et al. (2008: 419–420) distinguish a formative phase in which "the constituent elements of the new TIS begin to be put into place, involving entry of some firms and other organizations, the beginning of an institutional alignment and formation of networks" from a growth phase when "the focus changes to system expansion and large-scale technology diffusion through the formation of bridging markets and subsequently mass markets". While traditional TIS studies emphasize changes in the structure of innovation systems (e.g. Jacobsson, 2008), more recent work provides a functional analysis of influential processes in the early period including: knowledge creation, entrepreneurial experimentation, and influence on the direction of search (Hekkert et al., 2007; Bergek et al., 2008; Markard et al., 2012).

The innovation literature emphasizes some characteristics of the formative period such as: lengthy process (Klepper, 1997); experimentation (Arrow, 1962; Jacobsson and Lauber, 2006); coexistence of a range of competing designs (Abernathy and Utterback, 1978); high uncertainty regarding technologies, markets and institutions (Van de Ven, 2017; Kemp et al., 1998; Bergek et al., 2008). The focus on one or several of those formative features distinguishes theoretical approaches.

2.2. Duration

How long formative phases last depends on what is included in their scope. The *delimitation* of the formative phase also has a wide range of interpretation in the literature (see also Gustafsson et al., 2016).

Jacobsson and Lauber (2006: 260) suggest that the end of the formative phase "may occur when investments have generated a large enough, and complete enough, system for it to be able to 'change gears' and begin to develop in a self-sustaining way". Indicators of formative phase end point include the establishment of dominant designs (Abernathy and Utterback, 1978; Anderson and Tushman, 1990), industry "shake-outs" (Klepper, 1997), sales take-off—identified either by analyzing the evolution of annual rates (Agarwal and Bayus, 2002) or by comparing them with an empirically-derived take-off curve (Golder and Tellis, 1997; Tellis et al., 2003). Other studies estimate the end of the formative phase using a threshold like 2.5% market share, corresponding to the innovator segment of potential adopters (Rogers, 2003). This is consistent with research on new consumer products which shows evidence of market take-off at an average market penetration of 2.5–3% (Tellis et al., 2003; Golder and Tellis, 1997). Other thresholds such as 10–20% of total adoption have also been used to approximate the point of self-sustaining market growth (Mathur et al., 2007).

Clearly identifying a start point for formative phases is also problematic as definitions vary from recognized date of invention (Agarwal and Bayus, 2002; Hanna et al., 2015), or start of development (Kohli et al., 1999) to first commercialization (Golder and Tellis, 1997; Tellis et al., 2003; Smil, 2010).

Bento and Wilson (2016) test different indicators for the duration of the formative phase for a sample of technologies in their initial markets (Fig. 1). The central estimates assume the formative phase starts in the year of first sequential commercialization, and ends when diffusion reaches 2.5% of potential adopters (in line with Rogers' (2003) definition of "innovators"). Alternative indicators of formative phase start and end points reveal the uncertainty ranges. Results show the long time scale of formative phases, rarely shorter than a decade, varying from 4 years for fluid catalytic cracking in refineries to 85 years for stationary steam engines.

2.3. Determinants of duration

The duration of formative phases is shaped by both technology and market context. It is thus important to understand the factors associated with shorter and longer formative phases. Systemic theories such as the TIS perspective (Markard et al., 2012; Bergek et al., 2015) are concerned with structural elements underlying the emergence of new technologies, but are less clear on how these factors affect the duration

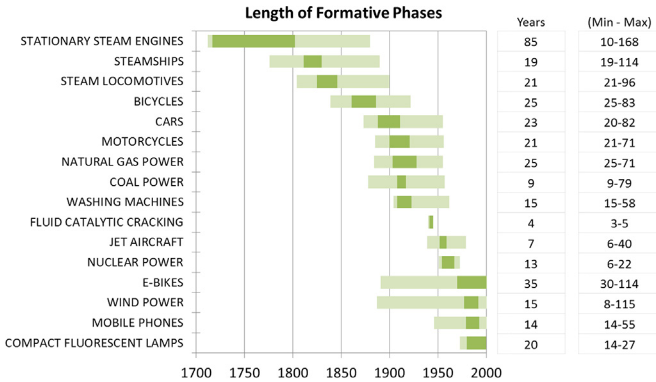

Fig. 1. Duration of formative phase for energy technologies. In decadal scale. Light green represents uncertainty ranges by using alternative indicators for start and end points of formative phases (cf. Bento and Wilson, 2016). See the methodological section for more details on indicators and data sources. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

of the formative phase.

The technology and market characteristics that determine the speed of diffusion may affect the duration of the formative phase as well. The most important determinant of adoption rates according to Rogers (2003) is relative advantage: the higher the performance, efficiency or price advantage over the incumbent technology, the faster the diffusion. Learning and cost reductions improve relative advantage in the early years, and reductions in price can be a sign of the formative phase ending (Chandrasekaran et al., 2013). Compatibility also influences adoption rates: the higher the compatibility with existing technologies, infrastructures and institutions, the faster the diffusion (Rogers, 2003). Other factors contribute to slow the pace of diffusion including complexity: the more learning needed to operate and produce, and the more interrelated a technology is, the slower the diffusion.

The takeoff literature has identified several factors that accelerate the early phase of diffusion, e.g.: price reductions; market penetration; product category ("brown products" such as CDs takeoff faster than "work products" such as home appliances), and cultural factors such as low uncertainty avoidance (Golder and Tellis, 1997; Tellis et al., 2003; Tellis and Chandrasekaran, 2012).

Other factors influencing formative phase duration include unit scale which affects the risks and resource requirements for repeated experimentation with multiple units in the early years (Winter, 2008; Wilson, 2012). Up-scaling of unit sizes and/or manufacturing is associated with the convergence on a dominant design and a clearly articulated market demand. In addition, market characteristics may influence the duration of the formative phase especially in the case of radical and novel technologies (Arthur, 2009), in which the diffusion process requires the creation of entirely new social, economic and cultural structures (e.g., standards, infrastructures, preferences)—rather than substitution of an existing technology to provide a similar service using the same infrastructure (see also Adner and Kapoor, 2010). The size of potential market also provides a measure of the challenges, for example: technologies that give rise to large systems (i.e. more pervasive) take longer to grow (Wilson et al., 2012).

We can distill these different arguments in the literature into testable hypotheses on formative phase duration which operationalize the causal effect of technology (H1, H2, H3) and adoption context (H4, H5):

Hypothesis 1: *Formative phase durations are longer for technologies with higher prices.*

Hypothesis 2: *Formative phase durations are longer for technologies with higher complexity.*

Hypothesis 3: *Formative phase durations are shorter for technologies with faster upscaling.*

Hypothesis 4: *Formative phase durations are longer for more pervasive technologies with larger market impact.*

Hypothesis 5: *Formative phase durations are shorter for substitute technologies which do not provide new services, require additional infrastructure, or open new markets.*

2.4. Spatial diffusion

Knowledge gained in initial markets may spillover to benefit formative processes in follower markets. Hagerstrand (1968) was the first to demonstrate that diffusion typically starts from innovative centers ('core´) and disseminates, through a hierarchy of subcenters, to the periphery. This process is sequential rather than simultaneous, and tends to accelerate from core to periphery, where diffusion reaches a lower intensity than in the core (Hagerstrand, 1968; Grubler, 1990; Morrill, 2005). A similar effect of spatial acceleration has been identified in marketing research and is known as the "lead-lag effect" (Peres et al., 2010).

Spatial diffusion influences the duration of formative phases. Deployment in core markets increases the knowledge stock related to the technology (e.g., cost, performance, designs, applications) that can 'spillover' to benefit latecomers (Perkins and Neumayer, 2005; Battke et al., 2016). Still, innovations do not spread automatically but require from the later adopters the capacity to absorb and assimilate the new technology and knowledge spillovers (Cohen and Levinthal, 1990, 1989). Institutional and organizational changes are needed to enhance local absorptive capacity for adopting new technologies (Bergek et al., 2015). Examples include the importance of early experimental projects to create system learning that accelerated the adoption of wind technologies in Portugal (Bento and Fontes, 2015), the role of industrial policy promoting both demand and supply in the development of wind energy in China (Surana and Anadon, 2015), and the difficulties for followers to assimilate knowledge spillovers in the case of solar energy technologies (Binz and Anadon, 2018; Binz et al., 2017).

Formative phases in follower countries can thus be accelerated by capturing knowledge spillovers (e.g. through experimentation for performance improvements codified in hardware), by developing local capacity (e.g. through experimentation for performance improvements embedded in tacit knowledge), or by appropriating elements from other TISs (e.g. skilled personnel, technology standards). Studies of energy technologies support the tendency for accelerated diffusion times in follower regions (Wilson and Grubler, 2015; Gosens et al., 2017; Binz et al., 2017; Surana and Anadon, 2015).

In sum, formative phase duration in later adopting regions is determined by the accelerating effect of knowledge spillovers and the time needed to adapt the technology to local conditions and create enough absorptive capacity in latecomer regions.

Hypothesis 6: *Formative phase durations are shorter in follower countries because of knowledge spillovers.*

Fig. 2 summarizes the hypothesized factors affecting formative phase durations, which we test empirically in the following sections.

3. Method: modeling the determinants of formative phase duration

3.1. Models

We assess the determinants of formative phase duration of technologies in different markets using parametric and non-parametric survival analysis. We use parametric analysis in core markets with lengthy formative phases as data is more available. We then use non-parametric analysis to compare formative phase durations in follower regions.

The (parametric) hazard model explains the event of finishing the

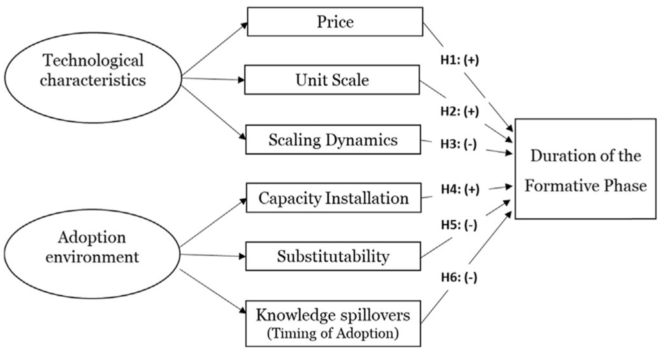

Fig. 2. Modeling the effect of technological and market drivers on the duration of the formative phase.

formative phase conditional on the change of covariates shown in Fig. 2. We use Cox's (1972) proportional hazard model which has the advantage of estimating the hazard ratios without specifying the baseline hazard, i.e. the effect of time since introduction of a technology (Wooldridge, 2010). This model has been used to analyze market take-off of consumer products in marketing studies (Golder and Tellis, 1997, 2004; Agarwal and Bayus, 2002; Chandrasekaran and Tellis, 2007; Tellis and Chandrasekaran, 2012). The model has the following representation:

$$h_i(t) = h(t; \boldsymbol{X}_{it}) = h_0(t)\exp(\boldsymbol{X}_{it}\,\beta)$$

where h_i (t) is the hazard of ending the formative phase of technology i, h_0 (t) is an unspecified baseline hazard function that depends on time only, $\boldsymbol{X}_{it}$ is the vector of independent variables of the technology i at time t (where t_0 and t_f are the start and end years of the formative phase, respectively), and β is the vector of coefficients to be estimated. The β measures the effect of covariates on the hazard function, which is captured by the hazard ratio exp(β). Positive β coefficients increase the hazard function and so the probability of ending the formative phase and negative β coefficients decrease the hazard of ending the formative phase. However, the interpretation of β is not straightforward. An increase of one unit in any independent variable results in a (exp(β) − 1) x 100% increase of the dependent variable (here the probability of ending the formative phase).

The dependent variable (hazard) is binary (0,1) and assumes the value one when a technology reaches 2.5% of its potential market share. This metric marks the end of the innovator segment in Rogers' (2003) adopter categories (see also Mahajan et al., 1990), and is the preferred metric of the end of the formative phase identified in a comparative analysis of different indicators (Bento and Wilson, 2016).

The independent variables affecting the duration of the formative phase include both technology and market characteristics (see Fig. 2).

Price is a time-dependent variable and a key determinant of a technology's relative advantage. It is measured in US $ per kW for comparison. Note that price typically declines with deployment but the dependent variable is a proportion of the potential market (2.5% market share), not the number of units or installed capacity. It is not possible to use prices relative to incumbent technologies because of diffusion processes in which new technologies introduce new services for which there are no clear incumbents.

Complexity refers to the degree of technology architecture and hierarchy of sub-components as operationalized in Murmann and Frenken (2006). Hobday (1998) also evaluates complex products and systems by looking at constituent dimensions. We use technology *unit scale* as a proxy of complexity because, ceteris paribus, larger scale technologies tend to have more levels and numbers of sub-components, raising the requirements (e.g. knowledge, learning) for production and use. *Initial Unit Scale* (of first commercialization) is a fixed variable that captures the effect of the size of a technology, in megawatts (MW). *Average Unit Scale* is a time-dependent variable that designates the mean capacity of annual unit additions and controls for the dynamic impacts of technology up-scaling, also in MW.

Cumulative Units is a time-dependent variable that records all the history of the number of installations up to a given point in time. These variables provide an estimate of the size of the system being developed. In addition, *Growth in Unit Sales* refers to the rate of increase in annual unit additions and accounts for the recent gains from experimentation and production with the last units (Arrow, 1962; Jacobsson and Lauber, 2006). Strong and sustained growth rates indicate the end of the formative phase according to Surana and Anadon (2015).

Substitute is a categorical variable that is assigned the value one in the case of innovations that replace existing technologies in existing markets (Garcia and Calantone, 2002). In contrast, diffusion processes involve new technologies with interdependent infrastructures and institutions (Grubler, 2012, 1998). In this study, the substitute technologies are product goods (compact fluorescent light bulbs (CFLs) and e-bikes), but also energy supply technologies (nuclear power and wind power) that benefited from their interaction with already existing electricity networks and markets (more details in Section 3.2 and Bento and Wilson, 2016).

The model also controls for the effect of other factors, namely type of technology and timing or year of introduction. *Type of technology* is a categorical variable that assumes the value one in the case of end-use technologies (compact fluorescent light bulbs (CFLs), cellphones, washing machines, bicycles, e-bikes, motorcycles, cars, jet aircrafts). These technologies convert energy into a useful final service such as

Table 1
Variable construction.

	Variables	Rationale for the introduction of the variables and metrics used	Measurement
Dependent variable	2.5% Market Share	Diffusion passes from the "innovators" category to larger groups of adopters (Rogers, 2003; Mahajan et al., 1990)	Share of maximum potential adopters
Independent variables	Price	Longer formative phase for technologies with lower price declines (Rogers, 2003)	US $ per kW
	Initial Unit Scale	Longer formative phases for large and complex innovations with several sub-components (Murmann and Frenken, 2006)	Unit scale of first commercialization in MW
	Average Unit Scale	Longer formative phases for technologies with slower up-scaling (Wilson, 2012)	Annual average unit scale in MW
	Cumulative Units	Longer formative phases for technologies diffusing into larger markets (Grubler, 1998, 2012)	Cumulative unit numbers
	Growth in Unit Sales	Longer formative phases for technologies with lower annual increase of demonstrations and deployment (Arrow, 1962; Jacobsson and Lauber, 2006)	Increase in annual unit additions in %
	Substitute	Longer formative phases for technologies which are not ready substitutes (Garcia and Calantone, 2002)	Substitute technology as 1, other as 0
Control variable	Type	Longer formative phases for energy supply technologies	End-use technology as 1, other as 0
	Year of Introduction	Longer formative phases for technologies introduced a long time ago	Year of introduction (or data availability of sales as a surrogate)

Table 2
Technologies, region definitions and key sources.

Technology	Data & Units	Time Series		Core	Market Potential *	Main Sources
		Costs	Installations			
Steam stationary	Costs, Total Capacity (#,hp)	1724–1900	1710–1930	UK, US	*power provided by different sources*	Kanefsky, Woytinsky, US Census
Steamships	Installed Capacity (#, hp)	–	1810–1940	UK, US	*gross tonnage of merchant vessel fleet (sail, steam, motor)*	Mitchell, Woytinsky, US Census
Steam locomotives	Costs, Installed Capacity (#, hp)	1828–1905	1830–1960	UK, US	*rail passenger traffic (million passengers)*	Woytinsky, US Census, Daugherty
Bicycles	Costs, Bicycles production (#, MW[e])	1892–2010	1861–2010	UK, France, Germany	*population*	UN, UK and US Census, INSEE, DIW
Coal Power	Costs, Capacity Additions (#, MW)	1971–2000	1908–2000	OECD	*number of power plants in use*	Platts
Natural Gas Power	Costs, Capacity Additions (#, MW)	1971–2000	1903–2000	OECD	*number of power plants in use*	Platts
Passenger Cars	Costs, Cars Produced (#) & Engine Capacity(hp)	1910–1927	1900–2005	US	*number of households*	AAMA, US NHTSA, ACEA
Washing machines	Washing machines production (#,MW[e])	–	1920–2008	US	*number of households*	UN, Stiftung Warentest
Motorcycles	Motorcycles production (#,MW[e])	1900–2008	1900–2008	UK, France, Germany, Italy	*number of households*	UN
Wind Power	Costs, Capacity Additions (#, MW)	1981–2009	1977–2008	Denmark	*electricity generation mix*	DEA, BTM Consult
Electric bicycles	Costs, E-bikes production (#,MW[e])	1999–2010	1997–2010	China	*number of households*	Weinert, Jamerson&Benjamin
Passenger Jet Aircraft	Aircraft Delivered (#, Model) & Engine Thrust (kN)	–	1958–2007	Boeing	*number of air carriers in service*	Jane's, aircraft databases
Nuclear Power	Costs, Capacity Additions (#, MW)	1972–1990	1956–2000	OECD	*total installed capacity*	Platts
Mobile Phones	Costs, Cellphones sales (#,MW[e])	1983–2009	1979–2010	Scandinavia, Japan	*population*	Gartner
Compact Fluorescent Light Bulbs	Costs, Light Bulb Sales (#MW[e])	1990–2003	1990–2003	OECD (exc. Japan)	*light bulb sales*	IEA

*Data for same initial markets as time series, except for: stationary steam engines (UK); jet aircraft (US); steamships (US); motorcycles (UK).
[e] Estimated.
Main sources show the principal references for time series of installations (unit numbers and installed capacity). For complete references on installations and costs, see Bento (2013) and Wilson (2009).

lighting, mobility or heating; in contrast, energy supply technologies extract and transform energy resources into more versatile forms of energy. End-use technologies dominate the energy system in terms of energy conversion capacity and investment, but directed innovation efforts privilege energy supply technologies (Wilson et al., 2012). Therefore this variable controls for any potential acceleration effect on the formative phase of energy supply technologies as a result of policy emphasis.

Year of Introduction refers to the start of (sequential) commercialization of a technology. This variable tests the effect of time, i.e. whether formative phases are becoming shorter as a result of exogenous technological change (Nordhaus, 2014; Mokyr, 2010). Table 1 summarizes the variables and measurements.

After using hazard models to test the determinants of formative phase duration in initial markets, we then use non-parametric analysis to compare the formative phase duration in follower markets. Specifically, we use Kaplan-Meier curves as a non-parametric statistic of the duration function, i.e. the time to end the formative phase. They show the proportion of technologies that remain (or "survive") in the sample since the year of start of (sequential) commercialization. Given that there is no censoring of observations—all technologies analyzed ended the formative phase—the Kaplan-Meier curves also provide the empirical distribution of data.

We use the software package survival in R for estimation, taking the robust standard errors clustered at the technology level. This allows for intra-technology correlation, relaxing the requirement of independence within groups.

3.2. Data and sources

The models were applied to a diverse sample of 15 energy technologies of varying vintages and characteristics: stationary steam engines; steamships; steam locomotives; bicycles; coal power plants; natural gas power plants; passenger cars; washing machines; motorcycles; wind power plants; electric bicycles; passenger jet aircrafts; nuclear power plants; mobile phones; compact fluorescent light bulbs. Table 2 presents the technologies in the sample, information on relevant markets and key sources of data. It also defines the core markets into which the technologies first diffused (see more details in Bento (2013) and Wilson (2009); data can be provided upon request).

4. Results

4.1. Formative phase duration in initial markets

Fig. 3 compares key innovation measures across the sample of 15 technologies at end points of their respective formative phases in initial markets only. Cumulative capacity and number of units provide information on experimentation and system size. Average unit scale indicates the complexity of technology production and usage (here shown relatively to the maximum unit scale identified ex post). Price is indexed to the introductory level when technologies were first commercialized and shows the cost reduction by the end of the formative phase when technologies reach 2.5% market share.

On average, cumulative unit numbers and cumulative installed capacity increase intensively (four and three orders of magnitude, respectively). Average unit scale rises about 50% across technologies. Prices decrease by 57% relatively to the introductory level. This is similar to the finding of Chandrasekaran et al. (2013), whose data for seven new consumer electronic products shows prices at take-off to be 52% of initial prices. These average values hide significant differences between the technologies as shown in Fig. 3. End-use technologies on average deploy more technologies and have deeper cuts in prices between formative phase start and end points (see Appendix A for further analysis).

We apply a hazard model to estimate the effect of the explanatory (independent) variables defined in the conceptual framework in

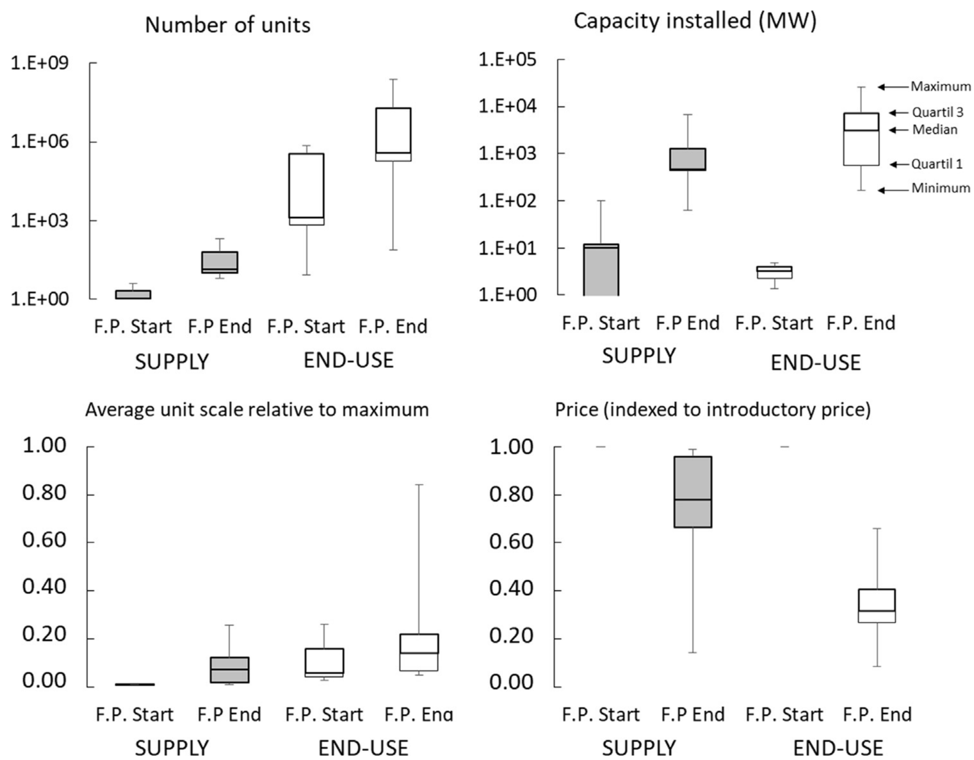

Fig. 3. Key indicators at formative phase start and end points in core markets, by type of technology (energy supply (n = 5) in shaded boxes, and end-use (n = 9) in unshaded boxes)*. *Bicycles are not included in the graphical analysis as not relevant for showing average capacity installed and unit capacity.

Table 3
Descriptive statistics and bivariate Pearson correlations.

	N	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. 2.5% Market Potential	1049	.67	.471	1									
2. Price	755	32,248	182,090	− .176**	1								
3. Initial Unit Scale	1049	7.42	18.555	.122**	− .103**	1							
4. Average Unit Scale	1049	47.385	182.516	.152**	− .045	.204**	1						
5. Cumulative Units	1049	60,671,717	310,579,930	.091**	− .002	− .078*	− .051	1					
6. Cumulative Capacity	1049	132,032	467,114	.199**	− .043	.080**	.047	.047	1				
7. Growth in Unit Sales	992	.43	4.52	− .11 * *	− .001	− .018	− .019	− .012	− .022	1			
8. Substitute	1049	.13	.334	− .257**	− .077*	− .054	.354**	.068*	− .088**	.068*	1		
9. Type	1049	.45	.498	.007	.214**	.082**	− .187**	.215**	.190**	.045	.026	1	
10. Year of Introduction	1049	1872	79.437	.063*	.181**	.318**	.218**	.197**	.110**	.038	.467**	.477**	1

* The bivariate Pearson correlation is significant at .05 level (bilateral).
** The bivariate Pearson correlation is significant at .01 level (bilateral).

accelerating the end of the formative phase (dependent variable) in core markets.

Table 3 presents the descriptive statistics of all (dependent and independent) variables, as well as their Pearson correlations. Correlations are generally low (i.e. below .3) and not significant among the independent variables.

We check for multicollinearity in the independent variables with a Variance Inflation Factor (VIF) test. The VIF values are below 5 for all covariates, indicating no significant problems of multicollinearity among the covariates. The time-dependent covariates are lagged one period to deal with autocorrelation following a current procedure in these analysis (e.g. Palacios Fenech and Tellis, 2016).

Table 4 presents the estimates of the Cox proportional hazard model for the end of the formative phase. Note that the model explains the effect of the covariates on the probability that the end of the formative phase (the event) happens at a particular point in time. This in turn determines the duration of the formative phase (as stated in the hypotheses). However it is important to note that the expected signs of the coefficients are the opposite of those in Fig. 2 as an increased probability of the formative phase ending is consistent with a shorter formative phase. As an example, price decreases are expected to reduce the duration of the formative phase, or alternatively, to increase the probability of the end of the formative phase occurring. The end occurs when a technology reaches 2.5% of market share (dependent variable). All models but one (model 3 with controls only) are statistically significant according to the *p-values* associated with the Wald test, therefore rejecting the null hypothesis that all the coefficients are equal to zero.

Table 4
Results of Cox proportional hazard model estimation of drivers of the formative phase (in Core).

		Dependent variable: 2.5% Market Share				
	Expected sign	1	2	3	4	5
Price (lag 1)	- (**H1**)	.0000*** (.00000)			.0000*** (.00000)	.0001*** (.00001)
Initial Unit Scale	- (**H2**)	− .011 (.006)			.030*** (.010)	− .003 (.012)
Average Unit Scale (lag 1)	+ (**H3**)	− .0003*** (.0002)			− .001*** (.0002)	− .001* (.0003)
Cumulative Units (lag 1)	- (**H4**)		− .000** (.000)		− .000 (.000)	− .000 (.000)
Growth in Unit Sales (lag 1)	+ (**H4**)		.021*** (.006)		.015** (.007)	.015*** (.018)
Substitute (1: Yes; 0: No)	+ (**H5**)		.531* (.098)		1.453*** (.167)	.937** (.244)
Type (1: End-use; 0: Others)	control			.032 (.069)	.407** (.129)	.633*** (.196)
Year of Introduction	control			− .001 (.0005)	− .005*** (.001)	− .002* (.001)
Price (lag 1) x Type	–					− .0001*** (.00001)
Initial Unit Scale x Type	–					− 307.792 (479.219)
Avg. Unit Scale (lag 1) x Type	–					− 2.441 (5.332)
Cumulative Units x Type	–					− .000 (.000)
Growth in Sales (lag 1) x Type	+					− .004 (.019)
Substitute x Type	+					.730* (.263)
Observations		745	992	1049	712	711
Concordance		.769	.754	.511	.855	.938
Pseudo-R^2		.038	.036	.002	.142	.283
Log Likelihood		− 4171	− 5839	− 6251	− 3913	− 3850
Wald Test		69.85***	32.23***	.42	156***	368.13***

Columns 1–5 report coefficients, robust standard errors clustered at technology level (in parentheses) and quality measures from Cox proportional hazard regression model estimations (using the Efron method) for drivers of formative phase of 15 technologies observed in core countries. Table 2 identifies technologies and sources. Database organizes time dependent variables, multiple events and characteristics, per technology, in multiple rows (or observations), each of which corresponding to an interval of a year, following the formulation of Andersen and Gill (Therneau and Grambsch, 2000). Number of observations can change due to missing values (mostly for technology price). Missing values are handled through listwise deletion, i.e., by not taking into account the respective lines in the model estimation. We test the assumption of proportional hazard which is not satisfied for several covariates. Some authors argue that this problem does not dismiss the model as such parameters represent "average effects" of the variable over time (Allison, 1995; Borucka, 2013). Thus we limit the interpretation of the effects, but conclusions can still be drawn from the signs of the coefficients to determine whether the covariate has a (significant) positive or negative effect in the dependent variable.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

Table 5
Standardized coefficients (ordered by absolute value).

	Model 4
Initial Unit Scale	1.02***
Substitute (1: Yes; 0: No)	.97***
Year of Introduction	− .74***
Price (lag 1)	.59***
Type (1: End-use; 0: Others)	.42**
Average Unit Scale (lag 1)	− .41***
Cumulative Units (lag 1)	− .15
Growth in Unit Sales (lag 1)	.13**

*$p < .1$.
** $p < .05$.
*** $p < .01$.

Model 1 regresses the dependent variable on important technology characteristics: price; initial unit scale; average unit scale (see H1-H3 in Fig. 2). According to the literature review, these variables should delay the end of the formative phase. The coefficients are significant (except for initial unit scale) and with expected signs. Model 2 examines the effect on the end of the formative phase of variables related to the system integration of technologies: growth in sales, cumulative installed units, and whether the technology is a ready substitute (see H4-H5 in Fig. 3). Again, the coefficients are significant and with expected signs. Model 3 investigates the effect of the control variables: type of technology (end-use or other) and year of introduction. The coefficients are not significant when regressed alone.

Model 4 is the base model containing all the main covariates and controls. Price, initial unit scale and average unit scale have a significant effect on the end of the formative phase. Larger, more expensive, technologies and technologies which upscale more rapidly have shorter formative phases. This result is against expectation. It is

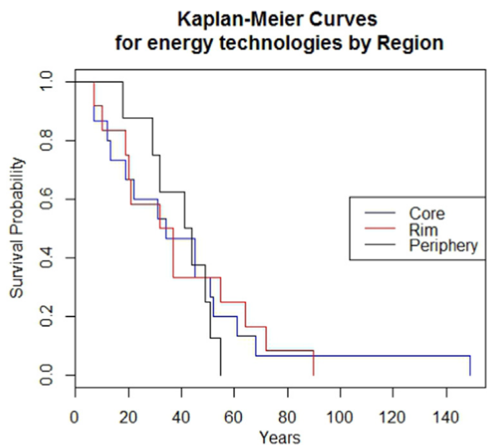

Fig. 4. Duration of formative phases across regions: Kaplan-Meier (nonparametric) estimator of the duration function. Technologies included in the Kaplan-Meier analysis: steam stationary; steamships; steam locomotives; bicycles; coal power; natural gas power; passenger cars; washing machines; motorcycles; wind power; electric bicycles; passenger jet aircraft; nuclear power; mobile phones; compact fluorescent light bulbs. End of the formative phase measured at 10% of the estimated maximum cumulative unit numbers as a proxy of 2.5% market share (cf. Bento and Wilson, 2016).

driven by two large scale technologies (nuclear power plants and jet aircrafts) which passed through fast formative phases associated with the very particular institutional environment of World War II which included price insensitive adoption and strong alignment between firms, government and users (Delina and Diesendorf, 2013).

Growth in annual sales increases the possibilities of experimentation and learning which accelerates the formative phase, as expected. Substitution processes also have a significant and strong effect on the probability of ending the formative phase.

End-use technologies have a significantly higher probability of reaching the end of the formative phase in shorter durations compared to other technologies. In contrast, the year of introduction has a significant but negative effect on the end of the formative phase, rejecting the argument that formative phases have accelerated over time with a gathering pace of technological change.

To compare the relative effects of variables measured in different units and scales, the coefficients need to be standardized so that the results are more easily comparable. We estimate the standardized beta coefficients in R, following Gelman's procedure of subtracting the mean of input variables and scaling them by two standard deviations (Gelman, 2008). This procedure leaves categorical coefficients unscaled because their coefficients can already be interpreted directly. Table 5 shows the standardized estimates for the main model (model 4). The interpretation of these estimates is as follows: a change of two standard deviations in the independent variable (or the difference between the two conditions for a categorical independent variable) produces a beta standard deviation change in the dependent variable. For instance, a two standard deviation increase in initial unit scale (e.g., from −1 to +1 standard deviation around the mean) leads to an increase of 1.02 standard deviations in the hazard of ending the formative phase—-however initial unit scale presents confounding effects in model 1 and model 4. This is the largest significant direct effect which is followed by (in descending order of the absolute value) substitute, year of introduction, price, type, (annual) average unit scale and (annual) growth in unit sales.

Model 5 re-estimates the base model including interaction terms between the main explanatory variables and type of technology to test whether there are significant differences in the effects (or coefficients) for end-use technologies. We find that the interaction between price and type of technology has a negative and significant effect. This implies that the influence of price reductions is more important in the case of end-use technologies.

We find no significant effects for the interaction between type of technology and the following covariates: initial unit scale; average unit scale; cumulative units; growth in sales. However, we find that the interaction between substitute processes and type of technology has a positive and significant effect. This implies that the influence of substitution processes are even stronger in the case of end-use technologies.

The quality of the fit can be assessed by the pseudo R-square. Model 4 has a pseudo R-square of .142 which increases to .283 in model 5 when re-estimating with interaction effects. These results are in line with prior literature (Chandrasekaran et al. (2013) report a pseudo R-square of .34; Tellis et al. (2003) report .18 for the complete model). In addition, the concordance is an indicator that measures the proportion of pairs of technologies in which the technology with a higher-value predictor ends the formative phase before the other technology with a lower-value predictor. The high values for concordance increase the confidence in our findings. Appendix C confirms the robustness of the results for a different measure of the dependent variable (10% of maximum cumulative unit numbers).

Table 6
Summary of definitions and findings.

Definition			
Formative phase:		*The early stage of development that prepares a new technology to emerge and become established in the market.*	
Determinants of the duration of the formative phase			
Theoretical Section	**Hypothesis**	**Description**	**Result *(Section 4.1 if not stated otherwise)***
Section 2.3	*1*	We expect formative phase durations to be longer for technologies with higher prices.	Confirmed price effect, stronger for end-use technologies
	2	We expect formative phase durations to be longer for (larger) technologies with higher complexity.	Not confirmed
	3	We expect formative phase durations to be shorter for technologies with faster upscaling.	Not confirmed
	4	We expect formative phase durations to be longer for (more pervasive) technologies with larger market impact.	Not confirmed
	5	We expect formative phase durations to be shorter for substitute technologies which do not provide new services, require additional infrastructure, or open new markets.	Confirmed substitutability effect
Section 2.4	*6*	We expect that formative phase durations to be shorter in follower countries because of knowledge spillovers.	Confirmed for periphery (Section 4.2)

4.2. Spatial differences in formative phase duration

The hazard model analyzes the determinants of formative phase duration in each technology's initial market. Extending this parametric analysis to follower markets is not possible due to the lack of available data in multiple markets for the full set of independent variables including knowledge spillovers. Consequently, we show (non-parametric) Kaplan-Meier curves for three regions marking spatial diffusion: core (initial markets analyzed in the hazard model); rim; periphery. The core-rim-periphery markets are defined for each technology based on adoption timings. To identify the end of the formative phase in the different regions, we use 10% of the estimated maximum cumulative unit numbers as a proxy of 2.5% market share (market potential is not available for all regions in rim and periphery).

The Kaplan-Meier curves in Fig. 3 show no clear tendency from core to rim, but a steeper curve in periphery indicates shorter formative phases. The "installation period" of a new technology (cf. Perez, 2002, 2016) can be shorter in periphery because of a lower resistance from incumbents associated with the previous technology or low requirements of infrastructure to create the local market (Grubler, 2012). Therefore, we find only weak evidence of formative phases accelerating from core to periphery (Hypothesis 6) (Fig. 4).

One interpretation of these results is that slow formative phases in follower regions indicate the difficulties of building the requisite technological and institutional capacity to compress for diffusion in new markets. In particular, it might be more difficult to short-circuit the accumulation of human and institutional capacity in the formative phase than to accelerate diffusion once formation is completed. This is examined further in Appendix B.

5. Discussion and conclusion

Different strands of the innovation literature cover the dynamics and determinants of formation and diffusion. In this paper, we develop a coherent theoretical framework on formative phase duration. We apply this framework to estimate the duration of the formative phase for a diverse sample of energy technologies, and test the determinants of varying durations using a hazard model. Table 6 summarizes the key definitions and findings.

The paper confirms that certain drivers of formative phase duration cited in the literature are positively associated with shorter formative phases whereas others are not. Despite the literature that points to the effect of cost reductions in the takeoff of consumers products (e.g. Chandrasekaran et al., 2013), this study finds a stronger effect of substitutability on ending the formative phase, i.e., the larger the extent to which the technology is substitutable the easier it is to have faster formative phases.

This study contributes to the literature in several ways. First, we establish a new theoretical framework specifically on the formative phase. Previous research provides insights about the patterns and drivers of innovation in the early years, but these are dispersed across different streams of the literature. We contribute to bring together the most relevant theories and concepts on the formation of technologies into a unified and coherent framework. We also help modeling of formative phases by clearly defining variables and providing parameterizations of different effect sizes.

Our modeling improves understanding of the factors that govern formative phase duration and so informs policy-makers about the potential levers for accelerating formative phases for new energy technologies. Policy-makers should be particularly aware of the long time scales (typically taking 2–3 decades) of formation of innovations which give weak signs (if at all) of acceleration. To accelerate the growth of technologies, policy-makers have particularly focused directed innovation efforts on energy-supply technologies (Wilson et al., 2012) but our results refute the advantages of this strategy. They should also pay attention to the risks involved in accelerating novel, large scale concepts in terms of the potential for high costs of experimentation and slow progress towards large-scale diffusion. In practice, policy-makers should diversify their technology policy and avoid focusing solely on radical innovations, such as carbon capture and sequestration, with large potential of low-carbon energy production but that have not yet entered into the formative phase.

Our analysis also offers valuable lessons about the potential and limits of accelerating innovation formation and diffusion in follower countries, namely by showing the limits of knowledge spillovers effects in streamlining the technological adaptation and local institutional build up necessary for the formative phases in new spaces. We only find evidence of formative phase acceleration in the transition of technologies to periphery. This is consistent with the results of recent research which suggests a harder catching up in the knowledge dimension of spatial technology diffusion (Binz et al., 2017). Policy-makers from countries that are typically fast followers need to pay attention to the conditions, namely in terms of the development of local knowledge, to accelerate innovation growth. Further research is needed to analyze more in detail the process of institutional build up in a multi-technology, multi-country framework.

Future work should test the findings with more technologies to understand the effect of prices on formative phase durations, as well as whether this effect is contingent on type and size of technologies. Finally, data on the covariates from several regions will allow for a spatial disaggregation of the effects, i.e. to understand the changes in the impact of variables in different regions, and the rates and extents of formative phases in follower regions.

Acknowledgments

The research on which this article is based was supported by a grant from the International Institute for Applied Systems Analysis (IIASA), and Harvard Kennedy School. Nuno Bento also acknowledges the postdoctoral grant (ref.SFRH/BPD/91183/2012) received from Fundação para a Ciência e a Tecnologia (FCT). Laura Diaz Anadon would like to acknowledge funding from the European Union's Horizon 2020 research and innovation programme (grant agreement 730403 – INNOPATHS). In addition, the authors would like to thank the participants in the 2016 ETH Academy, 2016 Dinâmia'Cet-IUL Workshop, 2017 APEEN Conference and 8th International Sustainability Transitions Conference, as well as Arnulf Grübler, Henry Lee, John Beshears, and Venkatesh "Venky" Narayanamurti for valuable insights. The usual disclaimers apply.

Appendix A

See Fig. A1.

Appendix A shows the changes in technology costs per capacity against cumulative installed capacity, which is the typical representation of learning curves, for six technologies. All technologies but nuclear power reduce costs per capacity over time. This pattern continues in subsequent stages with the exception of e-bikes for which the cost stabilize at the end of the formative phase. Nuclear power is a different case of negative learning largely due to knowledge obsolescence and increasing complexity with technology scale-up (e.g. stricter safety standards) (Grubler, 2010). Overall, experimentation and testing produce important learning and cost reductions in the formative phase.

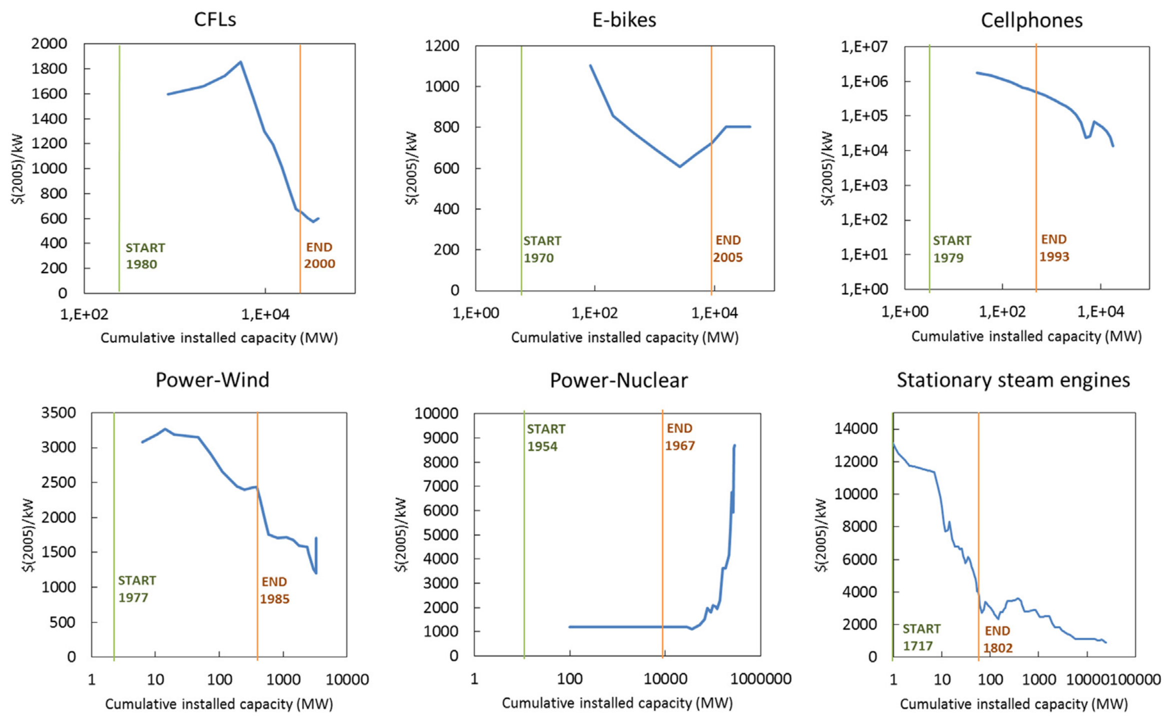

Fig. A1. Change in unit cost of technologies (US$(2005)/ kWeq.) with formative phase start and end points.

Appendix B

See Fig. B1.

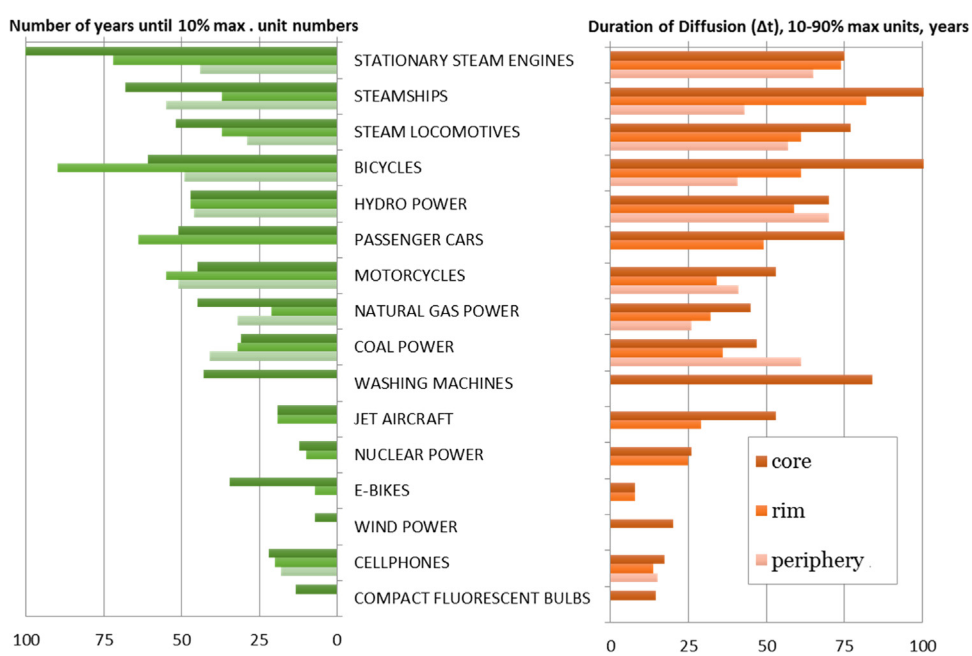

Fig. B1. Spatial differences in formative phases across regions.

The duration of diffusion is measured by the Δt—the time from 10% to 90% of saturation—which is inversely proportional to the rate of diffusion with higher Δt values meaning slower diffusion (see Wilson and Grubler, 2015). The time needed to reach 10% of total cumulative unit numbers (proxy of the formative phase—not available for rim and periphery) is almost as long as from 10% to 90% (diffusion) in all regions.

In addition, the diffusion accelerates in follower regions in 8 out of 13 technologies for which we have data for the different regions, whereas the period prior to diffusion is only shorter in followers in 5 out of 13 technologies.

Appendix C

See Table C1.

The analysis checks the robustness of the results from the previous models by re-estimating the base model 4 using an alternative proxy for the end of the formative phase based on 10% of cumulative unit numbers (see more details in Bento and Wilson, 2016). The coefficients are similar to the ones obtained by using the main dependent variable, underlining the stability of the results while reinforcing the confidence in the models.

Table C1
Robustness check.

Dependent variable: 10% Cumulative Units	Coefficient	Robust Standard Errors	P-value
Price (lag 1)	.000***	.000	.000
Initial Unit Scale	.020**	.010	.029
Average Unit Scale (lag 1)	− .001***	.0002	.000
Cumulative Capacity (lag 1)	− .0000***	.000	.000
Growth in Unit Sales (lag 1)	.011***	.003	.001
Substitute (1: Yes; 0: No)	.734***	.241	.002
Type (1: End-use; 0: Others)	.561**	.229	.014
Year of Introduction	− .008***	.001	. 000
Observations	712		
Concordance	.871		
Pseudo-R^2	.221		
Log Likelihood	− 3880		
Wald Test	242.62***		

Robust standard errors clustered at technology level. Cox proportional hazard regression model estimations using the Efron method for drivers of formative phase of 15 technologies observed in core countries. Note that we use here cumulative capacity rather than cumulative units like in Table 4 to avoid endogeneity with the dependent variable.
*p < .1.
** p < .05.
*** p < .01.

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